

11.Number of kids prediction - Preprocessing Data

- This is the collected data

Number of Kids	Working Expereince (years)	Age	Salary	Blood Types
3	15	45	\$250,000	A
1	5	30	\$200,000	B
2	10	38	\$150,000	AB
1	<missing>	36	\$180,000	O

1.Please clean the missing data using median approach.

- Pandas' Approach to replace the missing values of only one attribute: DataFrame's dropna(), drop(), and fillna() methods.
- Noticed that the Working Expereince attribute has some missing value, you can fix the issue by using DataFrame's dropna(), drop(), and fillna() methods:

Option 1: Get rid of the corresponding districts.

```
data.dropna(subset=["Working_Expereince"])
```

Option 2: Get rid of the whole attribute.

```
data.drop("Working_Expereince", axis=1)
```

Option 3: Set the missing values to some value (zero, # the mean, the median, etc.) on the training set

```
median = data["Working_Expereince"].median()
```

```
data["Working_Expereince"].fillna(median, inplace=True)
```

- The **mean** is the sum of all the numbers in the set (30) divided by the amount of numbers in the set (3) ==> **30/3 = 10**.
- The **median** is the middle point of a number set, in which half the numbers are above the median and half are below. In our Example the median = **10**.
- In the **case** of a high number of outliers in your dataset, it is recommended to use the **median instead of the mean**. Another common method that works for both numerical and nominal features use the most frequent **value** in the column to **replace the missing values**.

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➤ **Sciki-Learn's Approach to replace missing values of all attributes: Imputer.**

Step 1: Create an [Imputer](#) instance, specifying that you want to replace **each attribute's** missing values with the **median of that attribute**:

Step 2: Since the median can only be computed on numerical attributes, we need to create a copy of the data .

Step 3: Fit the **imputer** instance to the **training data** using the **fit()** method.

Step 4: The **imputer** has simply computed the median of each attribute and stored the result in its **statistics_** instance variable.

- Only the Working Experience attribute had missing values, but we cannot be sure that **there won't be any missing values in new data** after the system goes live, so it is safer to apply the **imputer** to all the numerical attributes:

imputer.statistics_

Step 5: Use this “trained” **imputer** to transform the **training set** by replacing missing values by the **learned medians**:

Program -

```
import numpy as np
from sklearn.impute import SimpleImputer
imp= SimpleImputer(missing_values=np.nan, strategy='median')
X = [[15], [5],[10],[np.nan]]
imp.fit(X)
```

```
print("statistics_ = ", imp.statistics_)  
print("median = \n",imp.transform(X)) #median
```

Output -

```
statistics_ = [10.]
```

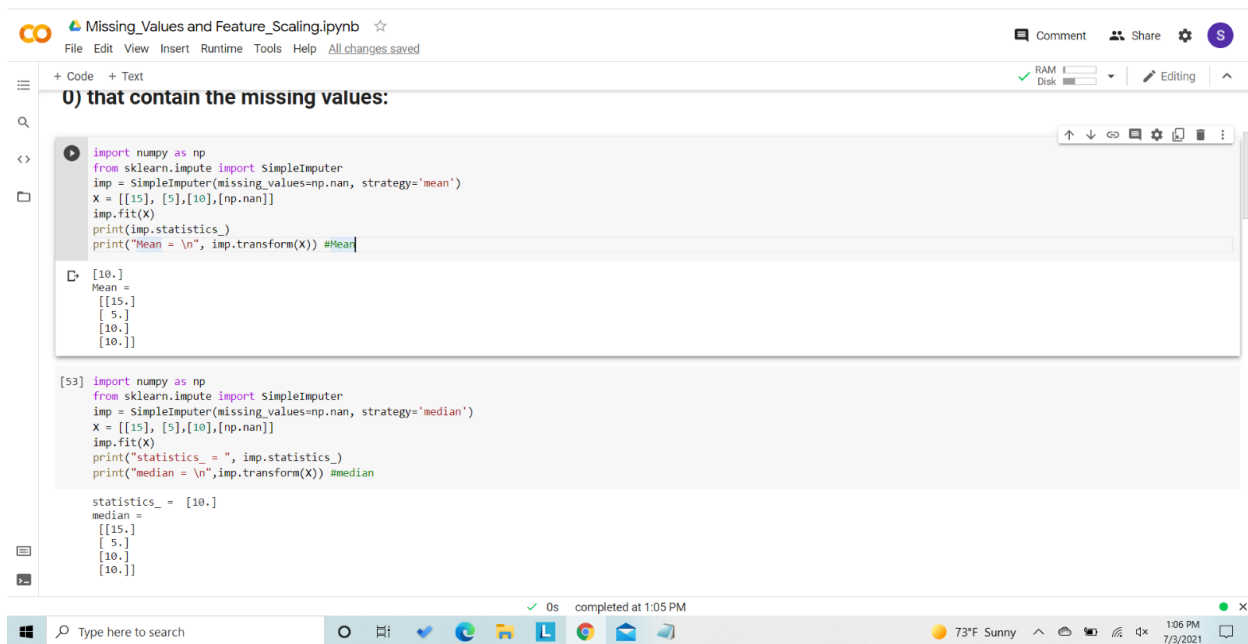
```
median =
```

```
[[15.]
```

```
[ 5.]
```

```
[10.]
```

```
[10.]] //Missing Value – Median
```



```
Missing_Values and Feature_Scaling.ipynb  
File Edit View Insert Runtime Tools Help All changes saved  
+ Code + Text  
0) that contain the missing values:  
import numpy as np  
from sklearn.impute import SimpleImputer  
imp = SimpleImputer(missing_values=np.nan, strategy='mean')  
X = [[15], [5],[10],[np.nan]]  
imp.fit(X)  
print(imp.statistics_)  
print("Mean = \n", imp.transform(X)) #Mean  
[10.]  
Mean =  
[[15.]  
[ 5.]  
[10.]  
[10.]]  
[53] import numpy as np  
from sklearn.impute import SimpleImputer  
imp = SimpleImputer(missing_values=np.nan, strategy='median')  
X = [[15], [5],[10],[np.nan]]  
imp.fit(X)  
print("statistics_ = ", imp.statistics_)  
print("median = \n",imp.transform(X)) #median  
statistics_ = [10.]  
median =  
[[15.]  
[ 5.]  
[10.]  
[10.]]
```

2.Please use Correlation to determine which of the following attributes is more related to "Number of Kids"?

- Working Experience
- Age

The correlation coefficient that indicates the strength of the relationship between two variables can be found using the following formula:

Definition

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

Where:

- r_{xy} – the correlation coefficient of the linear relationship between the variables x and y.
- x_i – the values of the x-variable in a sample.
- \bar{x} – the mean of the values of the x-variable.
- y_i – the values of the y-variable in a sample
- \bar{y} – the mean of the values of the y-variable

In order to calculate the correlation coefficient using the formula above, you must undertake the following steps:

- Obtain a data sample with the values of x-variable and y-variable.
- Calculate the means (averages) \bar{x} for the x-variable and \bar{y} for the y-variable.
- For the x-variable, subtract the mean from each value of the x-variable. Do the same for the y-variable.
- Multiply each $(x_i - \bar{x})$ value by the corresponding y-value and find the sum of these multiplications (the final value is the numerator in the formula).
- Square each $(x_i - \bar{x})$ value and calculate the sum of the result
- Find the square root of the value obtained in the previous step (this is the denominator in the formula).
- Divide the value obtained in step 4 by the value obtained in step 7.

➤ **Find the correlation coefficient of the linear relationship between the variables x (Number of Kids) and y (Working Experience).**

Number of Kids -> x_i	Working Experience (years) -> y_i	$x_i - \bar{x}$	$y_i - \bar{y}$	$(x_i - \bar{x}) * (y_i - \bar{y})$	$(x_i - \bar{x})^2$	$(y_i - \bar{y})^2$
3	15	1.25	5	6.25	1.5625	25
1	5	-0.75	-5	3.75	0.5625	25
2	10	0.25	0	0	0.0625	0
1	10	-0.75	0	0	0.5625	0

Mean(\bar{x}) 1.75	Mean(\bar{y}) 10	=	Sum	10	2.75	50
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Using the obtained numbers, can calculate the coefficient between the variables x (**Number of Kids**) and y (**Working Experience**) is :

$$r_{xy} = 10 / \sqrt{2.75 * 50} = 0.85280286542$$

- Find the correlation coefficient of the linear relationship between the variables x(**Number of Kids**) and y (**Age**).

Number of Kids - > xi	Age -> yi	xi - \bar{x}	yi - \bar{y}	(xi - \bar{x}) * (yi - \bar{y})	(xi - \bar{x})²	(yi - \bar{y})²
3	45	1.25	7.75	9.6875	1.5625	60.06
1	30	-0.75	-7.25	5.4375	0.5625	52.5625
2	38	0.25	0.75	0.1875	0.0625	0.5625
1	36	-0.75	-1.25	0.9375	0.5625	1.5625
Mean(\bar{x}) = 1.75	Mean(\bar{y}) = 37.25	Sum		16.25	2.75	114.75

Using the obtained numbers, can calculate the coefficient between the variables x(**Number of Kids**) and y (**Age**) :

$$r_{xy} = 16.25 / \sqrt{2.75 * 114.75} = 0.91476738366$$

The coefficient indicates that the following attributes “Working Experience” and “Age” have a high positive correlation. This means that their respective chances that the both attributes belong to the Number of Kids. Therefore, compare to both attributes, in fact, **Age attribute is more related to "Number of Kids"**.

3. Please use One-Hot Vectors approach to convert the **Blood Types**.

Convert text categorical attribute “Blood Types” to be able to compute its median.

Step 1: Convert from text categories to integer categories

Note: One issue with Categorical Value representation is that ML algorithms will assume that two nearby values are more similar than two distant values.

Step 2: Convert from integer categories to One-Hot Vectors.

For example -

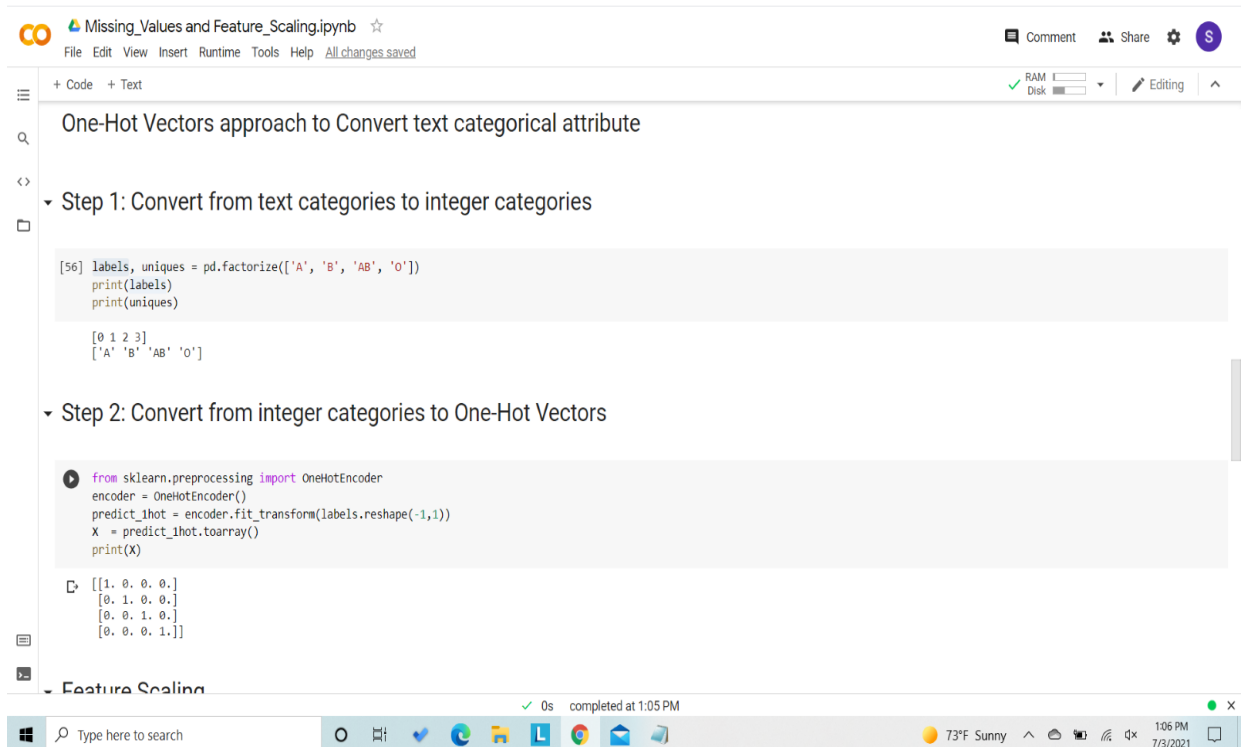
Number of Kids	Working Expereince (years)	Age	Salary	Blood Types
3	15	45	\$250,000	A
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2	10	38	\$150,000	AB
1	10	36	\$180,000	O

Step 1: Convert from text categories “Blood Types” to integer categories

Number of Kids	Working Expereince (years)	Age	Salary	Blood Types	Categorical Value
3	15	45	\$250,000	A	1
1	5	30	\$200,000	B	2
2	10	38	\$150,000	AB	3
1	10	36	\$180,000	O	4

Step 2: Convert from integer categories to One-Hot Vectors.

Number of Kids	Working Experience (years)	Age	Salary	Blood Types	A	B	AB	O
3	15	45	\$250,000	A	1	0	0	0
1	5	30	\$200,000	B	0	1	0	0
2	10	38	\$150,000	AB	0	0	1	0
1	10	36	\$180,000	O	0	0	0	1



```
[56] labels, uniques = pd.factorize(['A', 'B', 'AB', 'O'])
      print(labels)
      print(uniques)

[0 1 2 3]
['A' 'B' 'AB' 'O']
```

```
from sklearn.preprocessing import OneHotEncoder
encoder = OneHotEncoder()
predict_1hot = encoder.fit_transform(labels.reshape(-1,1))
X = predict_1hot.toarray()
print(X)
```

```
[[1. 0. 0. 0.]
 [0. 1. 0. 0.]
 [0. 0. 1. 0.]
 [0. 0. 0. 1.]]
```

4. Please use Standard Scale to scale the data.

Feature Scaling using Standardization.

- **Standardization.**

Scikit-Learn provides a transformer called [StandardScaler](#) for **standardization**.

Process

- Step 1: It subtracts the **mean** value (so **standardized values** always have a **zero mean**).
- Step 2: It divides by the **variance** so that the resulting distribution has **unit variance**.
- Standardization is much less affected by **outliers**.

1. Input Data -

1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

2. Calculate the **mean** for the input data using below Formula -

$$\mu = \frac{1}{N} \sum_{i=1}^N (x_i)$$

Here x_i = values of the input data

Note:

- $0.25 = (1 + 0 + 0 + 0)/4$
- $0.25 = (0 + 1 + 0 + 0)/4$
- $0.25 = (0 + 0 + 1 + 0)/4$
- $0.25 = (0 + 0 + 0 + 1)/4$

0.25 0.25 0.25 0.25

3. Calculate the **Standard deviation** using Below Formula -

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2}$$

Here x_i = values of the input data

u = Mean

Note:

- $0.433 = \text{sqrt}(((1-0.25)^2 + (0-0.25)^2 + (0-0.25)^2 + (0-0.25)^2) / 4)$
- $0.433 = \text{sqrt}(((0-0.25)^2 + (1-0.25)^2 + (0-0.25)^2 + (0-0.25)^2) / 4)$
- $0.433 = \text{sqrt}(((0-0.25)^2 + (0-0.25)^2 + (1-0.25)^2 + (0-0.25)^2) / 4)$
- $0.433 = \text{sqrt}(((0-0.25)^2 + (0-0.25)^2 + (0-0.25)^2 + (1-0.25)^2) / 4)$

0.433 0.433 0.433 0.433

4. Calculate the **scaled data** using below Formula -

$$z = \frac{x - \mu}{\sigma}$$

X = values of the input data

and **u** = mean and **σ** = Standard deviation

Note:

- $1.732 = (1 - 0.25) / 0.433$
- $-0.577 = (0 - 0.25) / 0.433$
- $-0.577 = (0 - 0.25) / 0.433$
- $-0.577 = (0 - 0.25) / 0.433$ //Likewise calculate for remaining values

Data after scaling -

1.732	-0.577	-0.577	-0.577
-0.577	1.732	-0.577	-0.577
-0.577	-0.577	1.732	-0.577
-0.577	-0.577	-0.577	1.732

5. Check the **mean** of the scaled data

$$\mu = \frac{1}{N} \sum_{i=1}^N (x_i)$$

Note:

- $0.00025 = (1.732 - 0.577 - 0.577 - 0.577) / 4$
- $0.00025 = (-0.577 + 1.732 - 0.577 - 0.577) / 4$
- $0.00025 = (-0.577 - 0.577 + 1.732 - 0.577) / 4$
- $0.00025 = (-0.577 - 0.577 - 0.577 + 1.732) / 4$

0.00025 0.00025 0.00025 0.00025

6. Check the **standard deviation** of the scaled data

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2}$$

Note:

- $0.99982632866 = \sqrt{(((1.732 - 0.00025)^2 + ((-0.577 - 0.00025)^2) * 3) / 4)}$
- $0.99982632866 = \sqrt{(((1.732 - 0.00025)^2 + ((-0.577 - 0.00025)^2) * 3) / 4)}$
- $0.99982632866 = \sqrt{(((1.732 - 0.00025)^2 + ((-0.577 - 0.00025)^2) * 3) / 4)}$
- $0.99982632866 = \sqrt{(((1.732 - 0.00025)^2 + ((-0.577 - 0.00025)^2) * 3) / 4)}$

1 1 1 1

The screenshot shows a Jupyter Notebook titled "Missing_Values and Feature_Scaling.ipynb". The code cell [58] imports StandardScaler from sklearn.preprocessing, fits it to data X, and prints the scaled data. The output is a 4x4 array of scaled values. Below the code, two verification steps are shown: checking the mean of each feature column (output: array([-5.55111512e-17, -5.55111512e-17, -2.77555756e-17, -5.55111512e-17])) and checking the standard deviation of each feature column (output: array([1., 1., 1., 1.])).

```
[58] from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
# fit and transform the data
scaled_data = scaler.fit_transform(X)
print(scaled_data)

[[ 1.73205081 -0.57735027 -0.57735027 -0.57735027]
 [-0.57735027  1.73205081 -0.57735027 -0.57735027]
 [-0.57735027 -0.57735027  1.73205081 -0.57735027]
 [-0.57735027 -0.57735027 -0.57735027  1.73205081]]
```

▼ Verify that the mean of each feature (column) is 0:

```
scaled_data.mean(axis = 0)
array([-5.55111512e-17, -5.55111512e-17, -2.77555756e-17, -5.55111512e-17])
```

▼ Verify that the std of each feature (column) is 1:

```
[60] scaled_data.std(axis = 0)
array([1., 1., 1., 1.])
```

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